

Applying Artificial Intelligence (AI) Based Signal Coordination and Controls for Optimized Mobility for the Nimitz Highway

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Oak Ridge National Laboratory Project ID: EEMS090

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2021 Vehicle Technologies
Annual Merit Review
June 2021

Overview

Timeline

- Project start date: 01 Feb 2021
- Project end date: 31 Jan 2023
- Percent complete: 16.7%

Budget

- Total project funding: \$2M
 - DOE share: \$2M
 - Contractor share: 0
- Funding for FY 2021: \$700k
- Funding for FY 2022: \$900k
- Funding for FY 2023: \$400k

Barriers and Technical Targets

- Barriers addressed
 - Data quality: we applied pre-filtering algorithm to improve the data for the modeling using neural networks
 - Large model parameters: We developed hybrid neural network to reduce model parameters
 - Real-time implementation

Partners

- Interactions/collaborations: University of Hawaii, Econolite Systems, Hawaii DOT
- Project lead: ORNL



1. Relevance

Impact:

- Since traffic systems are dynamic, nonlinear and stochastic, this project will develop AI-based modeling and controls for the first-time on 24/7 real-world implementation.
- Address the effects of future mobility technologies and services on VTO's research portfolio and thus significantly expend the DOE landscape for real-world implementation of AI for Mobility.
- Use data sources and facilities built via the recent investment from the Hawaii DOT to its busiest arterial for improved traffic system monitoring and operation.

Objective:

- Develop and apply AI based modeling and control for Optimized Mobility for the Nimitz Highway and Ala Moana Boulevard Arterial in Honolulu
- Operate the AI based modeling and control 24/7 as a real-time implementation to see the benefit of advanced signal controls

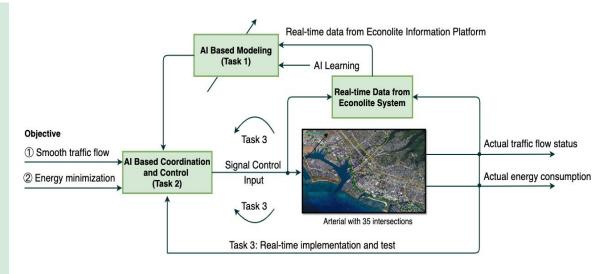


Figure 1. The closed loop system structure and tasks



Tasks and Milestones (Project duration on 02/01/2021 - 01/31/2023)

Milestone	Description	When	Status
Al-based modeling	Complete AI-based modeling for the Nimitz Highway and Ala Moana Boulevard arterial in Honolulu with a <10% modeling error and a 95% confidence interval	Month 5	In progress
Al-based control	Al-based control strategy completed with a <5% closed-loop control error, 15% energy savings, and 25% reduced travel delays for simulated scenarios. Go/no-go: Successful completion of Al-based modeling and control design	Month 12	Not started
Real-world testing	Complete the implementation of the AI-based control for the Nimitz Highway and Ala Moana Boulevard arterial in Honolulu with at least 15% energy savings and 25% of travel delay reduction compared with the baseline case of Econolite controls. Submit a paper to a leading transportation journal.	Month 24	Not started

2. Approach (Feb 2021 – now)

Data from Econolite Platform

High resolution data available from the platform as shown in Fig 2.

Neural Network Modeling

Use neural networks to model the dynamics of the intersections for travel delays and signal timing. The following modeling exercises have been conducted since Feb 2021:

- Linear (intersection # 4)
- Neural Network (intersection # 4)
- Hybrid Neural Network 1 (intersection # 4)
- Hybrid Neural Network 2 (7 intersections)

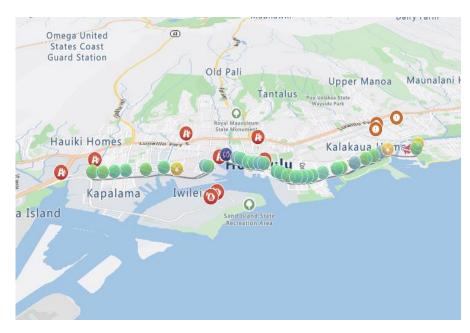
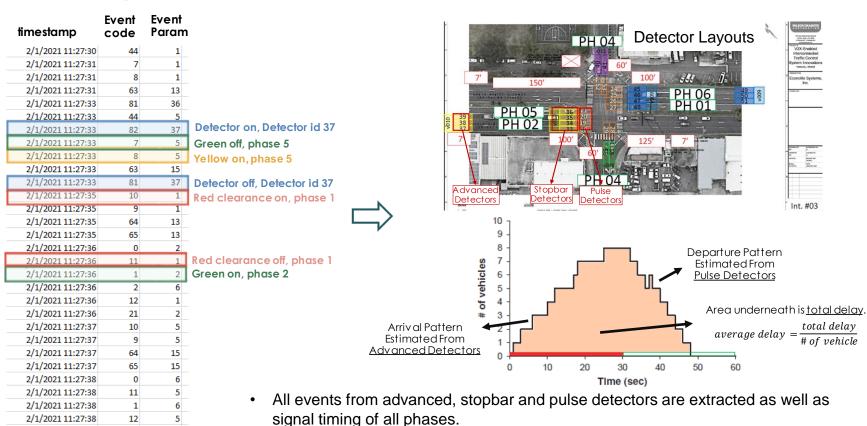


Figure 2. Econolite data and intersectional controls

3. Technical Accomplishments and Progress (since February 2021)

3.1 Obtain High-Resolution Delay Data from Econolite System

2/1/2021 11:27:20



• Queue length of each phase is estimated to calculate delay.

3.2 Linear System Modeling: Is the System Nonlinear?

Objective: To explore whether the system is linear or nonlinear

The intersection 4" is considered with the input as the green time and output as average per vehicle delays, denoted respectively as u(k) and y(k).

k = sample index once every 5 cycles.

The model is assumed to be the 1st order of the following structure

$$y(k+1) = ay(k) + bu(k) + \omega(k)$$

where $\{a, b\}$ are unknown parameters to be estimated, $\omega(k)$ is a noise.

Denote

$$\theta = \begin{bmatrix} a \\ b \end{bmatrix}, \quad \varphi(k) = \begin{bmatrix} y(k) \\ u(k) \end{bmatrix}$$

Then the following recursive least squares (RLS) algorithm is used to estimate $\{a, b\}$ using the data collected from Econolite/UH platform

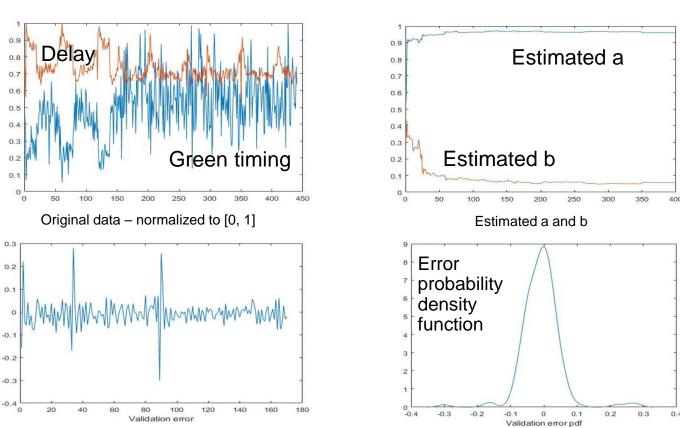
$$\theta(k+1) = \theta(k) + \frac{P(k)\varphi(k)\varepsilon(k)}{1 + \varphi^{T}(k)P(k)\varphi(k)}$$
$$\varphi^{T}(k) = [y(k)u(k)]$$
$$\varepsilon(k) = y(k+1) - \theta^{T}(k)\varphi(k)$$
$$P^{-1}(k+1) = P^{-1}(k) + \varphi(k)\varphi(k)^{T}$$

where

- $\theta(k)$ is the estimate of θ at sample time k (of every 5 cycles),
- P(k) is the variance matrix,
- $\varepsilon(k)$ is the estimation residual.

3.2 Linear Model Results – First Order Dynamics

The following figures shows the modeling results, $\theta(0) = 0$, $P(0) = 100I_{2\times 2}$



3.3 Hybrid Neural Network (HNN) Model - Multiple Intersections

- Study area: Intersection 1-7
- Date: March 3-5, 8-12, 15-19, 22-26, 29-31, April 1-2 (23 weekdays)
- **Time**: 4pm 7 pm
- Signal phase: all phases of major and minor streets
- Traffic volume: all movements
- Delay: all movements
- Sample Index: 5 signal cycles (Each cycle ≈170s)

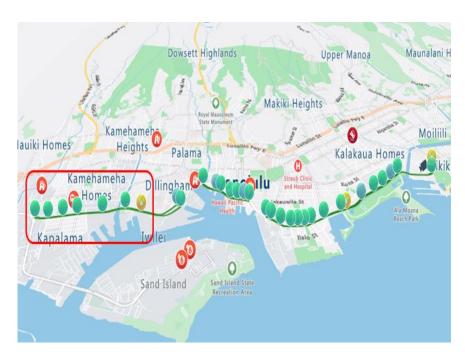
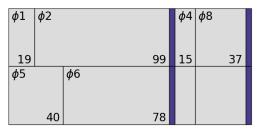


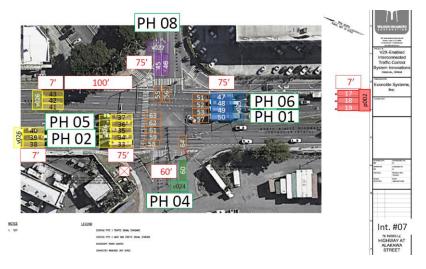
Figure 3. The First 7 intersections along Nimitz Highway

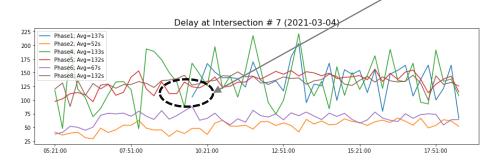


3.3 Hybrid NN Model - Data Visualization

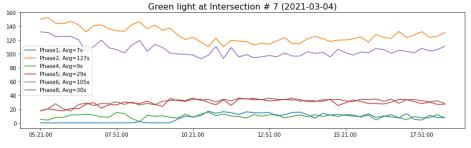
6 phases:

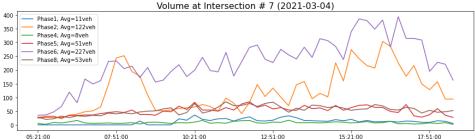






Missing data





3.3 Hybrid Neural Network (HNN) Modeling - Model Structure

HNN Model

Linear Nonlinear Term y(k+1) = Ay(k) + Bu(k) + f(y(k), u(k-1), v(k))Traffic volume $(1) \quad \text{HNN}$

where y(k) and u(k) denote average delay per vehicle and green time for multiple intersections at time index k. $\omega(k)$ is noise. {A, B} are the weight matrix. Let f(y(k), u(k-1), v(k)) be approximated and learned by $\hat{f}(y(k), u(k-1), v(k), \pi)$ using the real-time data, and v(k) denote traffic volume.

This is Achieved by minimizing Eq.(3) using gradient approach.

$$Min J = \frac{1}{2}(\hat{y}(k+1) - y(k+1))^2$$
 (2)

Objective

$$\hat{y}(k+1) = Ay(k) + Bu(k) + \hat{f}(y(k), u(k-1), v(k), \pi)$$
 (3)

 $\{A, B, \pi\}$ are parameters to be trained. π groups all NN weights and bias.

3.3 Hybrid NN - Model Training Algorithm

• Model parameters {A, B, π } are trained simultaneously by (6)-(11):

$$\hat{A}(k+1) = \hat{A}(k) - \lambda_1 \frac{\partial J}{\partial A}|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))}$$
(6)
$$\hat{B}(k+1) = \hat{B}(k) - \lambda_2 \frac{\partial J}{\partial B}|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))}$$
(7)
$$\hat{\pi}(k+1) = \hat{\pi}(k) - \lambda_3 \frac{\partial J}{\partial \pi}|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))}$$
(8)

where λ_1 , λ_2 , λ_3 are learning rates.

$$\frac{\partial J}{\partial A}|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1)) \frac{\partial \hat{y}}{\partial A}|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1)) y(k) \quad (9)$$

$$\frac{\partial J}{\partial B}|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1)) \frac{\partial \hat{y}}{\partial B}|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1)) u(k) \quad (10)$$

$$\frac{\partial J}{\partial \pi}|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1)) \frac{\partial \hat{f}}{\partial \pi}|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} \quad (11)$$

where y(k+1) is the measured data.



3.3 Hybrid NN – Experiment Results

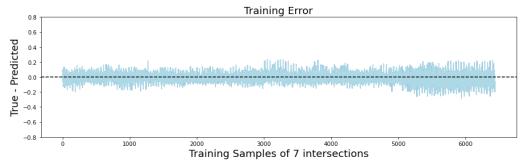
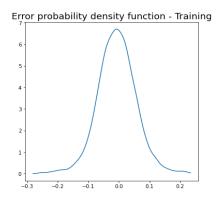


TABLE 1: Training and Testing Results

	Training (all)	Testing (all)	Testing (Main streets)	Testing (Side streets)
Mean Absolute Percentage Error (MAPE)	6.31%	6.51%	5.67%	6.98%
Rooted Mean Square Error (RMSE)	9.62 s	10.18 s	4.14 s	12.33 s
Mean Absolute Error (MAE)	6.72 s	6.99s	3.03s	9.21 s

TABLE 2: Testing results at each intersection

Intersection	1	2	3	4	5	6	7
Mean Absolute Percentage Error (MAPE)	4.03%	5.09%	5.7%	7.74%	7.75%	6.74%	6.12 %
Rooted Mean Square Error (RMSE)	3.79s	5.74s	10.76s	11.03s	12.61s	8.86s	10.30s
Mean Absolute Error (MAE)	2.29s	4.36s	6.65s	8.72s	9.18 s	6.23s	7.60s



$$MAPE = \frac{1}{NK} \sum_{k=1}^{K} \sum_{n=1}^{N} \left| \frac{y_n(k) - \hat{y}_n(k)}{y_n(k)} \right|$$

$$RMSE = \frac{1}{NK} \sum_{k=1}^{K} \sum_{n=1}^{N} \sqrt{(y_n(k) - \hat{y}_n(k))^2}$$

$$MAE = \frac{1}{NK} \sum_{k=1}^{K} \sum_{n=1N} |y_n(k) - \hat{y}_n(k)|$$

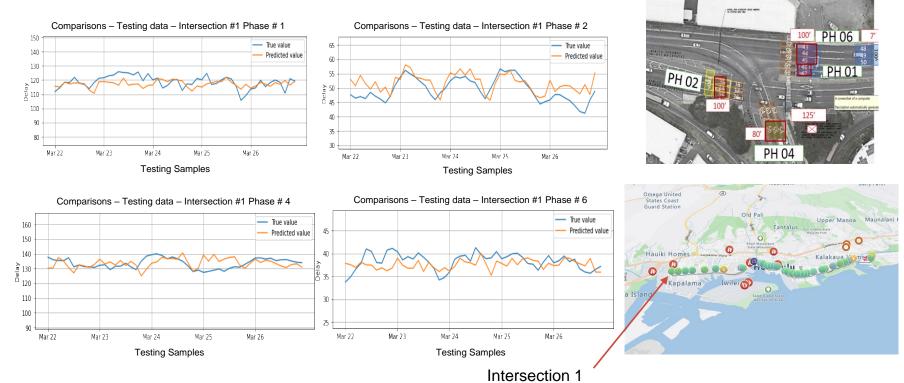
 $y_n(k)$: True delay at time k of phase n.

 $\hat{y}_n(k)$: Predicted delay at time k of phase n.



3.3 Hybrid Neural Network Modeling – Experiment Results

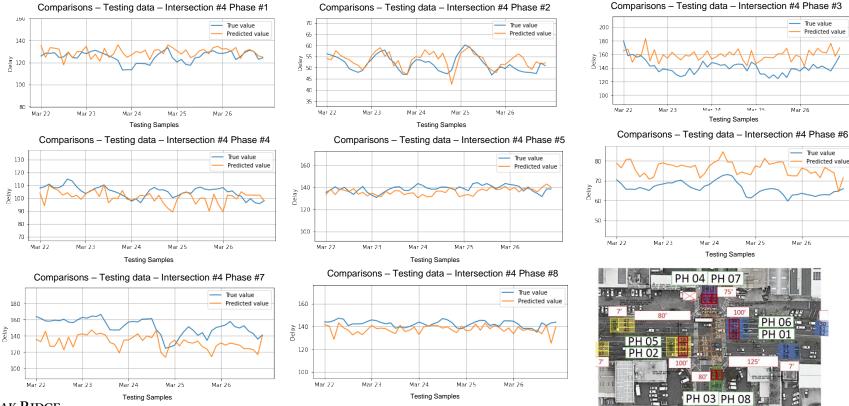
Testing: Intersection 1 (March 22 - 26), Total cycle length = 180 (sec)





3.3 Hybrid Neural Network Modeling – Experiment Results

Testing: Intersection 4 (March 22 - 26)



— True value

Mar 26

Mar 26

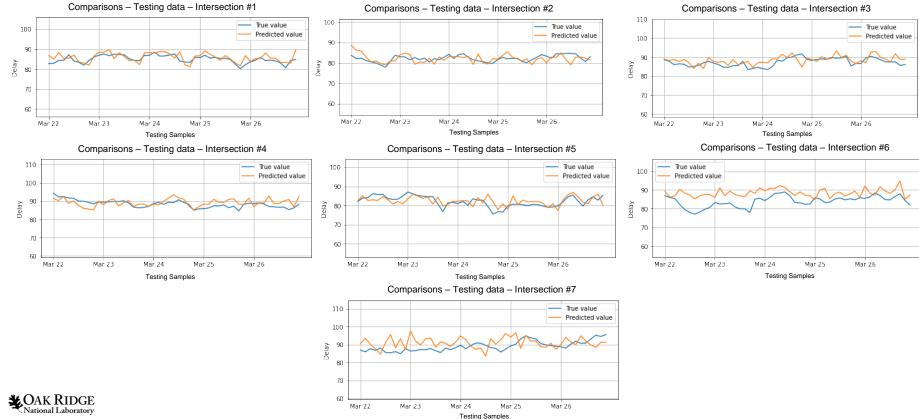
— True value

Predicted value

Predicted value

3.3 Hybrid NN – Experiment Results

Testing: Average travel delays at all 7 intersections



4. Collaborations and Coordination with Other Institutions

The project team is composed of ORNL, University of Hawaii, Econolite Systems and Hawaii DOT, where ORNL team lead the project and will work on Al-modeling, control design and leads 24/7 real-time implementation.

The collaborative activities are as follows:

- University of Hawaii (Professor Guohui Zhang and Dr Arun Bala Subramaniyan):
 - Data processing
 - Neural network modeling and VISSIM simulation
- Econolite Systems (Dr Jon Ringler):
 - Data collection and processing
 - Real-time modeling and control interface
 - Probability density function shaping for modeling error
- Hawaii DOT (Edwin H Sniffen):
 - Facilitates 24/7 implementation
 - Provides 10+ vehicles with onboard units to real-time testing

ORNL Team Members:

Dr Chieh (Ross) Wang

Dr Wan Li

Dr Yunli Shao

Dr Tim Laclair

Dr David Smith

Dr Jacky Rios-Torres



5. Remaining Challenges and Barriers

Most studies on AI for intersectional signal control only consider a few intersections, and no real-time learning system has been deployed for large-scale field testing because of the lack of comprehensive real-time data and user-friendly interfaces to the implementation. These shortcomings have limited the current research on AI for mobility at the simulation level.

Moreover, energy efficiency has not been well addressed for these Al-based modeling and controls. This constitutes the following challenges and technical barriers:

- Although the theory of Al-based modeling and control for signal control is maturing, the field testing and closed-loop control implementation for large number of intersections is still limited because of the insufficient real-time data for fast feedback control realization;
- The existing AI-based modeling for transportation systems cannot yet capture the nonlinear and dynamic stochastic nature with high reliability and robustness; and
- Guaranteed control performance for the energy minimization is still lacking.

The project therefore focuses on the development and implementation of real-time learning and adaptation for the signal control along the arterial, where both NN modeling and control will be adaptively learned during the real-time system operations.



6. Planned Future Research

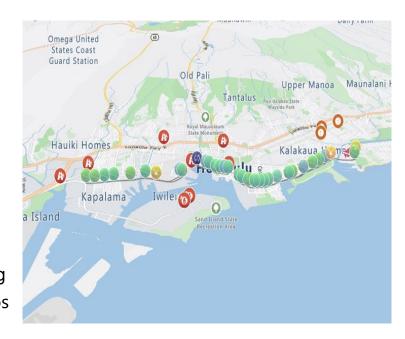
Data Processing

- Collect more data to train HNN
- Include signal phases for both major and minor streets
- Include more features, e.g., traffic volume.

Neural Network Modeling

- Complete HNN modeling for all the 34 intersections
- Use Different NN structures, e.g., RNN, LSTM.
- Use different sample intervals, e.g., every 2-4 cycles
- Explore probability density function shaping for modeling
- Validate data processing output with ground truth videos
- Al Controller Design (July 2021 Feb 2022)
- Real-time implementation (March 2022 Jan 2023)

Any proposed future work is subject to change based on funding levels.



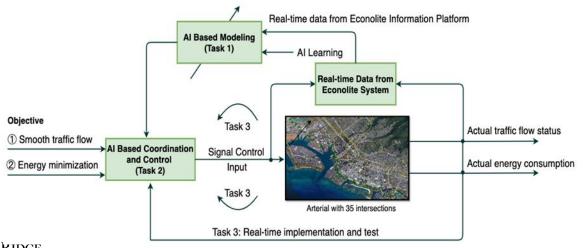
7. Summary

Accomplishments

 Complete AI-based modeling for the 7 intersections along Nimitz Highway and Ala Moana Boulevard arterial with a <10% modeling error as expected.

Technical Highlights

- Modeled the relationships between travel delay and signal timings using linear system modeling
- Developed a hybrid neural network modeling algorithm together with relevant training strategy
- Modeled the relationships between travel delay, signal timings, traffic volumes with hybrid neural network.



Thank you for your attention